Lecture 6: CNNs and Deep Q Learning [1]

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CS234 Reinforcement Learning.

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[1] With many slides for DQN from David Silver and Ruslan Salakhutdinov and some vision slides from Gianni Di Caro and images from Stanford CS231n, http://cs231n.github.io/convolutional-networks/

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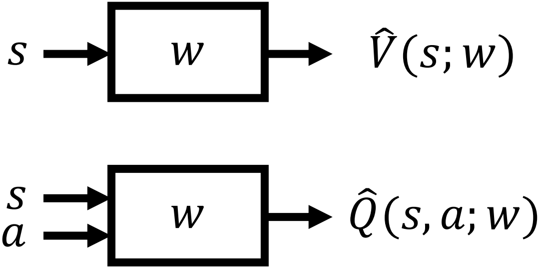
Class Structure

- Last time: Value function approximation
- This time: RL with function approximation, deep RL

Generalization

- Want to be able to use reinforcement learning to tackle self-driving cars, Atari, consumer marketing, healthcare, education, ...
- Most of these domains have enormous state and/or action spaces
- Requires representations (of models / state-action values / values / policies) that can generalize across states and/or actions
- Represent a (state-action/state) value function with a parameterized function instead of a table



Recall: Stochastic Gradient Descent

- Goal: Find the parameter vector $\boldsymbol{w}$ that minimizes the loss between a true value function $V^\pi(s)$ and its approximation $\hat{V}^\pi(s;\boldsymbol{w})$ as represented with a particular function class parameterized by $\boldsymbol{w}$.
- Generally use mean squared error and define the loss as

$$J(\boldsymbol{w}) = \mathbb{E}_\pi[(V^\pi(s) - \hat{V}^\pi(s;\boldsymbol{w}))^2]$$

- Can use gradient descent to find a local minimum

$$\Delta \boldsymbol{w} = -\frac{1}{2}\alpha \nabla_{\boldsymbol{w}} J(\boldsymbol{w})$$

- Stochastic gradient descent (SGD) samples the gradient:

$$-\frac{1}{2}\nabla_{\boldsymbol{w}} J(\boldsymbol{w}) = \mathbb{E}_\pi[(V^\pi(s) - \hat{V}^\pi(s;\boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{V}^\pi(s;\boldsymbol{w})]$$

$$\Delta \boldsymbol{w} = \alpha(V^\pi(s) - \hat{V}^\pi(s;\boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{V}^\pi(s;\boldsymbol{w})$$

- Expected SGD is the same as the full gradient update

Last Time: Linear Value Function Approximation for Prediction With An Oracle

- Represent a value function (or state-action value function) for a particular policy with a weighted linear combination of features

$$\hat{V}(s;\boldsymbol{w}) = \sum_{j=1}^{n} x_j(s) w_j = \boldsymbol{x}(s)^T \boldsymbol{w}$$

- Objective function is

$$J(\boldsymbol{w}) = \mathbb{E}_\pi[(V^\pi(s) - \hat{V}(s;\boldsymbol{w}))^2]$$

- Recall weight update is

$$\Delta \boldsymbol{w} = -\frac{1}{2}\alpha \nabla_{\boldsymbol{w}} J(\boldsymbol{w})$$

Last Time: Linear Value Function Approximation for Prediction With An Oracle

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$$\hat{V}(s; \boldsymbol{w}) = \sum_{j=1}^{n} x_j(s) w_j = \boldsymbol{x}(s)^T \boldsymbol{w}$$

- Objective function is $J(\boldsymbol{w}) = \mathbb{E}_\pi[(V^\pi(s) - \hat{V}^\pi(s; \boldsymbol{w}))^2]$
- Recall weight update is $\Delta \boldsymbol{w} = -\frac{1}{2}\alpha \nabla_{\boldsymbol{w}} J(\boldsymbol{w})$
- For MC policy evaluation

$$\Delta \boldsymbol{w} \;\; = \;\; \alpha(G_t - \boldsymbol{x}(s_t)^T \boldsymbol{w})\boldsymbol{x}(s_t)$$

- For TD policy evaluation

$$\Delta \boldsymbol{w} \;\; = \;\; \alpha(r_t + \gamma \boldsymbol{x}(s_{t+1})^T \boldsymbol{w} - \boldsymbol{x}(s_t)^T \boldsymbol{w})\boldsymbol{x}(s_t)$$

RL with Function Approximator

- Linear value function approximators assume value function is a weighted combination of a set of features, where each feature a function of the state
- Linear VFA often work well given the right set of features
- But can require carefully hand designing that feature set
- An alternative is to use a much richer function approximation class that is able to directly go from states without requiring an explicit specification of features
- Local representations including Kernel based approaches have some appealing properties (including convergence results under certain cases) but can't typically scale well to enormous spaces and datasets

Deep Neural Networks (DNN)

- Composition of multiple functions
- Can use the chain rule to backpropagate the gradient
- Major innovation: tools to automatically compute gradients for a DNN

Deep Neural Networks (DNN) Specification and Fitting

- Generally combines both linear and non-linear transformations
  - Linear:
  - Non-linear:
- To fit the parameters, require a loss function (MSE, log likelihood etc)

The Benefit of Deep Neural Network Approximators

- Linear value function approximators assume value function is a weighted combination of a set of features, where each feature a function of the state
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- But can require carefully hand designing that feature set
- An alternative is to use a much richer function approximation class that is able to directly go from states without requiring an explicit specification of features
- Local representations including Kernel based approaches have some appealing properties (including convergence results under certain cases) but can't typically scale well to enormous spaces and datasets
- Alternative: Deep neural networks
    - Uses distributed representations instead of local representations
    - Universal function approximator
    - Can potentially need exponentially less nodes/parameters (compared to a shallow net) to represent the same function
    - Can learn the parameters using stochastic gradient descent

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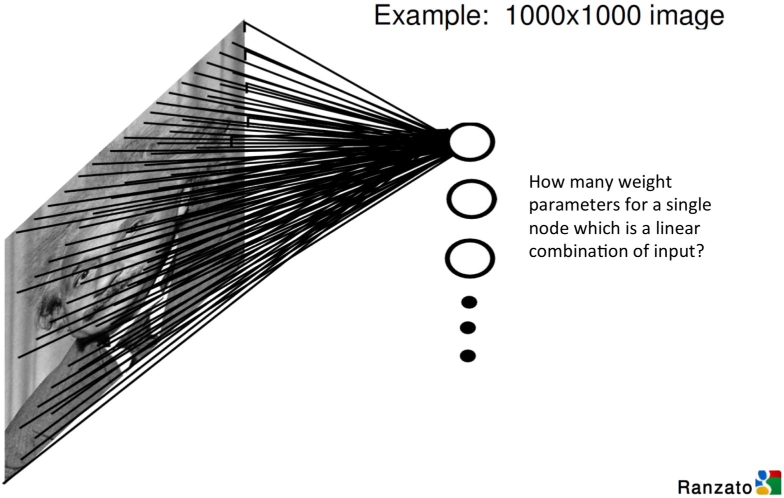
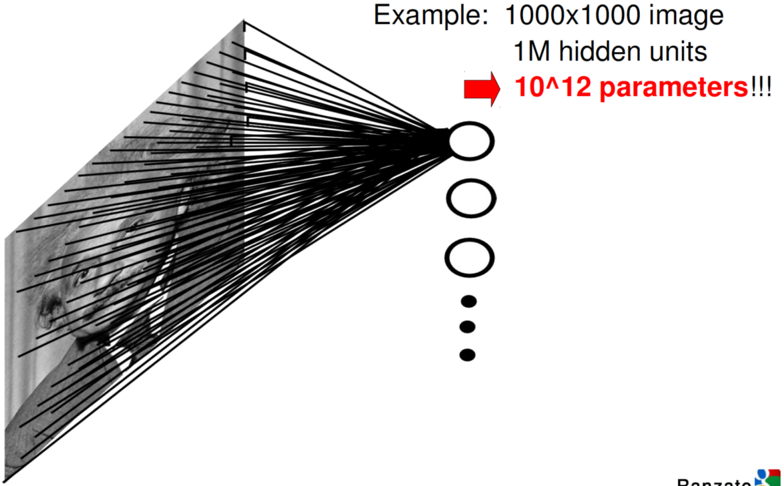
Why Do We Care About CNNs?

- CNNs extensively used in computer vision
- If we want to go from pixels to decisions, likely useful to leverage insights for visual input

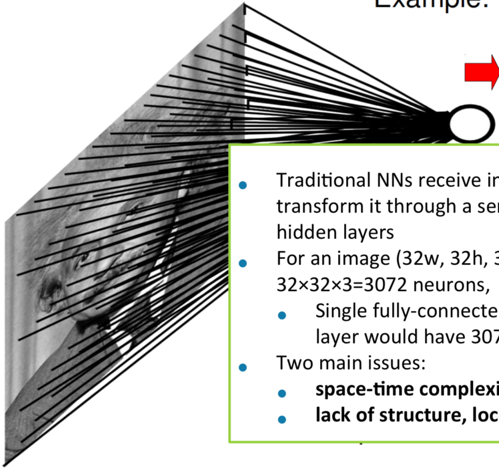
Fully Connected Neural Net



Fully Connected Neural Net



Fully Connected Neural Net



Example: 1000x1000 image
1M hidden units
10^12 parameters!!!

- Traditional NNs receive input as single vector & transform it through a series of (fully connected) hidden layers
- For an image (32w, 32h, 3c), the input layer has 32×32×3=3072 neurons,
  - Single fully-connected neuron in the first hidden layer would have 3072 weights …
- Two main issues:
  - **space-time complexity**
  - **lack of structure, locality of info**

Ranzato

Images Have Structure

- Have local structure and correlation
- Have distinctive features in space & frequency domains

Convolutional NN

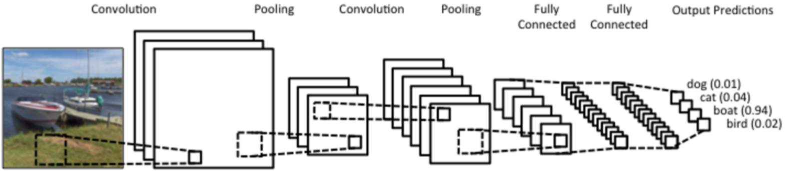
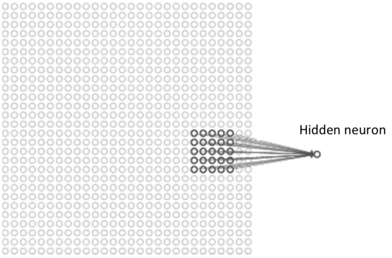
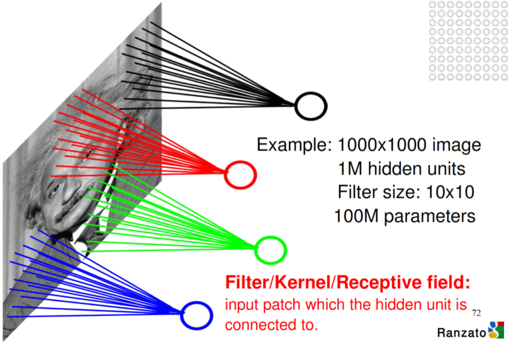


Image: http://d3kbpzbmcynnmx.cloudfront.net/wp-content/uploads/2015/11/Screen-Shot-2015-11-07-at-7.26.20-AM.png

- Consider local structure and common extraction of features
- Not fully connected
- Locality of processing
- Weight sharing for parameter reduction
- Learn the parameters of multiple convolutional filter banks
- Compress to extract salient features & favor generalization

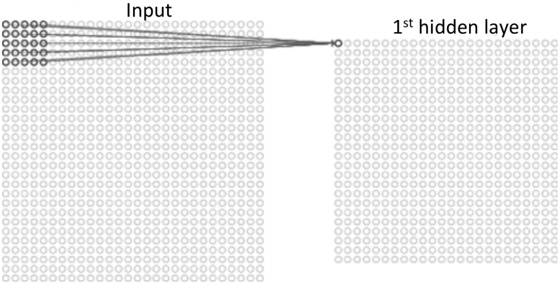
Locality of Information: Receptive Fields





(Filter) Stride

- Slide the 5x5 mask over all the input pixels
- Stride length = 1
  - Can use other stride lengths
- Assume input is 28x28, how many neurons in 1st hidden layer?



- Zero padding: how many 0s to add to either side of input layer

Shared Weights

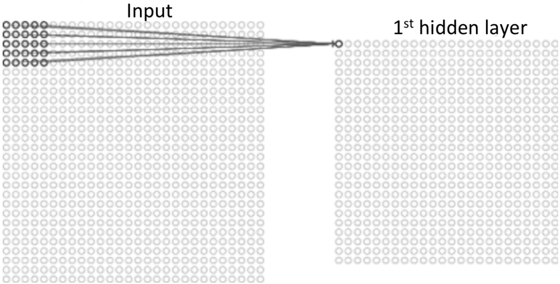
- What is the precise relationship between the neurons in the receptive field and that in the hidden layer?
- What is the *activation value* of the hidden layer neuron?

$$g(b + \sum_i w_i x_i)$$

- Sum over i is *only over the neurons in the receptive field* of the hidden layer neuron
- *The same weights w and bias b* are used for each of the hidden neurons
  - In this example, 24×24 hidden neurons

Ex. Shared Weights, Restricted Field

- Consider 28x28 input image
- 24x24 hidden layer

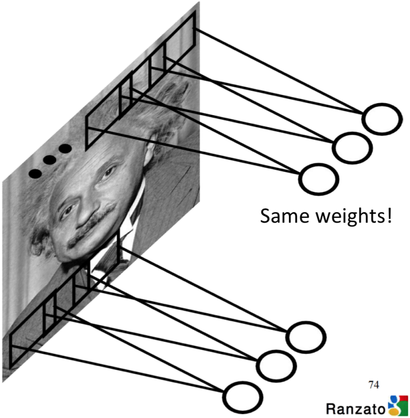


- Receptive field is 5x5

Feature Map

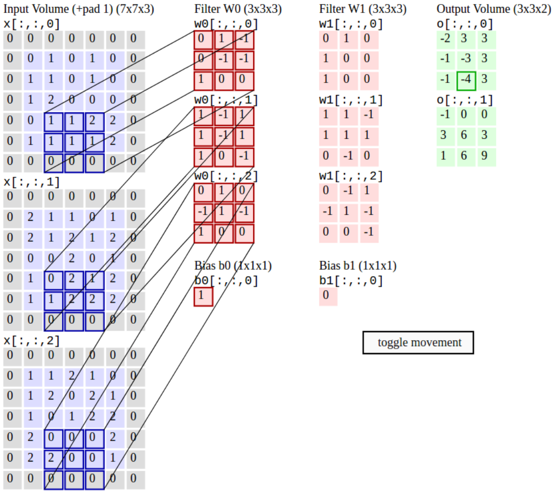
- All the neurons in the first hidden layer *detect exactly the same feature, just at different locations* in the input image.
- **Feature**: the kind of input pattern (e.g., a local edge) that makes the neuron produce a certain response level
- Why does this makes sense?
  - Suppose the weights and bias are (learned) such that the hidden neuron can pick out, a vertical edge in a particular local receptive field.
  - That ability is also likely to be useful at other places in the image.
  - Useful to apply the same feature detector everywhere in the image. Yields translation (spatial) invariance (try to detect feature at any part of the image)
  - Inspired by visual system

Feature Map



- The map from the input layer to the hidden layer is therefore a feature map: all nodes detect the same feature in different parts
- The map is defined by the shared weights and bias
- The shared map is the result of the application of a convolutional filter (defined by weights and bias), also known as convolution with learned kernels

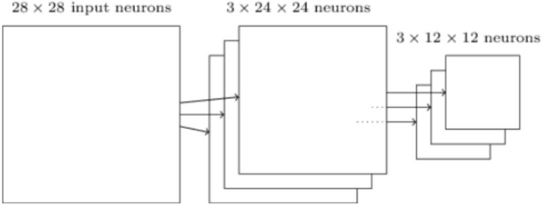
Convolutional Layer: Multiple Filters Ex.[1]



[1] http://cs231n.github.io/convolutional-networks/

Pooling Layers

- Pooling layers are usually used immediately after convolutional layers.
- Pooling layers simplify / subsample / compress the information in the output from convolutional layer
- A pooling layer takes each feature map output from the convolutional layer and prepares a condensed feature map



Final Layer Typically Fully Connected

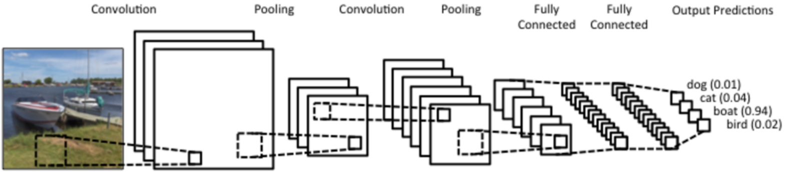


Image: http://d3kbpzbmcynnmx.cloudfront.net/wp-content/uploads/2015/11/Screen-Shot-2015-11-07-at-7.26.20-AM.png

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Generalization

- Using function approximation to help scale up to making decisions in really large domains

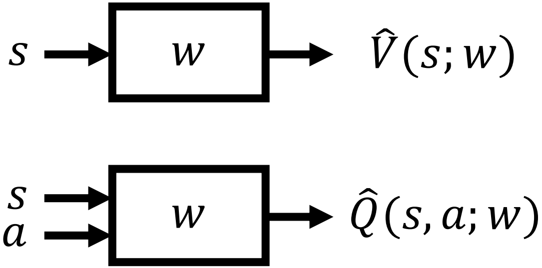
Deep Reinforcement Learning

- Use deep neural networks to represent
  - Value function
  - Policy
  - Model
- Optimize loss function by stochastic gradient descent (SGD)

Deep Q-Networks (DQNs)

- Represent state-action value function by Q-network with weights $\boldsymbol{w}$

$$\hat{Q}(s, a; \boldsymbol{w}) \approx Q(s, a)$$



Recall: Action-Value Function Approximation with an Oracle

- $\hat{Q}^\pi(s, a; \boldsymbol{w}) \approx Q^\pi$
- Minimize the mean-squared error between the true action-value function $Q^\pi(s, a)$ and the approximate action-value function:

$$J(\boldsymbol{w}) = \mathbb{E}_\pi[(Q^\pi(s, a) - \hat{Q}^\pi(s, a; \boldsymbol{w}))^2]$$

- Use stochastic gradient descent to find a local minimum

$$\begin{aligned} -\frac{1}{2}\nabla_{\boldsymbol{W}} J(\boldsymbol{w}) &= \mathbb{E}_\pi\left[(Q^\pi(s, a) - \hat{Q}^\pi(s, a; \boldsymbol{w}))\nabla_{\boldsymbol{w}}\hat{Q}^\pi(s, a; \boldsymbol{w})\right] \\ \Delta(\boldsymbol{w}) &= -\frac{1}{2}\alpha\nabla_{\boldsymbol{w}} J(\boldsymbol{w}) \end{aligned}$$

- Stochastic gradient descent (SGD) samples the gradient

Recall: Incremental Model-Free Control Approaches

- Similar to policy evaluation, true state-action value function for a state is unknown and so substitute a target value
- In Monte Carlo methods, use a return G_t as a substitute target

$$\Delta \boldsymbol{w} = \alpha(G_t - \hat{Q}(s_t, a_t; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s_t, a_t; \boldsymbol{w})$$

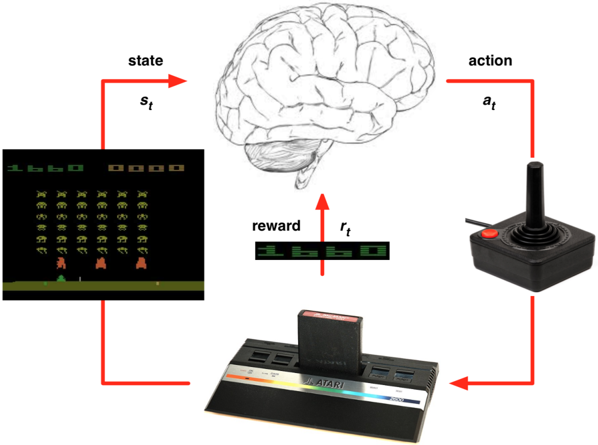
- For SARSA instead use a TD target $r + \gamma \hat{Q}(s_{t+1}, a_{t+1}; \boldsymbol{w})$ which leverages the current function approximation value

$$\Delta \boldsymbol{w} = \alpha(r + \gamma \hat{Q}(s_{t+1}, a_{t+1}; \boldsymbol{w}) - \hat{Q}(s_t, a_t; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s_t, a_t; \boldsymbol{w})$$

- For Q-learning instead use a TD target $r + \gamma \max_a \hat{Q}(s_{t+1}, a; \boldsymbol{w})$ which leverages the max of the current function approximation value

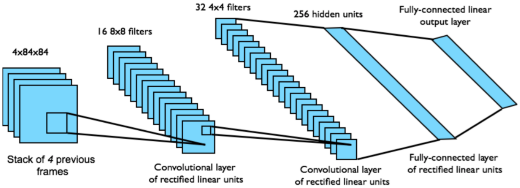
$$\Delta \boldsymbol{w} = \alpha(r + \gamma \max_a \hat{Q}(s_{t+1}, a; \boldsymbol{w}) - \hat{Q}(s_t, a_t; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s_t, a_t; \boldsymbol{w})$$

Using these ideas to do Deep RL in Atari



DQNs in Atari

- End-to-end learning of values $Q(s, a)$ from pixels s
- Input state s is stack of raw pixels from last 4 frames
- Output is $Q(s, a)$ for 18 joystick/button positions
- Reward is change in score for that step



- Network architecture and hyperparameters fixed across all games

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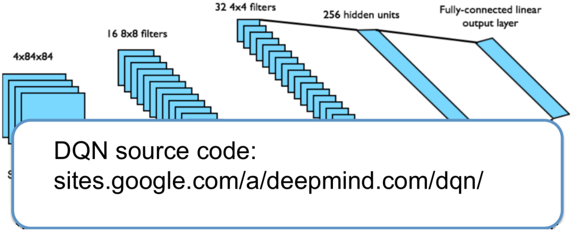


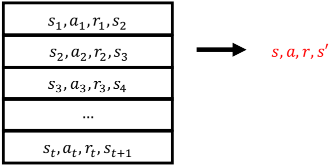
DQN source code:
sites.google.com/a/deepmind.com/dqn/

- Network architecture and hyperparameters fixed across all games

Q-Learning with Value Function Approximation

- Minimize MSE loss by stochastic gradient descent
- Converges to the optimal $Q^*(s, a)$ using table lookup representation
- But Q-learning with VFA can diverge
- Two of the issues causing problems:
  - Correlations between samples
  - Non-stationary targets
- Deep Q-learning (DQN) addresses both of these challenges by
  - Experience replay
  - Fixed Q-targets

- To help remove correlations, store dataset (called a **replay buffer**) $\mathcal{D}$ from prior experience



- To perform experience replay, repeat the following:
  - $(s, a, r, s') \sim \mathcal{D}$: sample an experience tuple from the dataset
  - Compute the target value for the sampled s: $r + \gamma \max_{a'} \hat{Q}(s', a'; \boldsymbol{w})$
  - Use stochastic gradient descent to update the network weights

$$\Delta \boldsymbol{w} = \alpha(r + \gamma \max_{a'} \hat{Q}(s', a'; \boldsymbol{w}) - \hat{Q}(s, a; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s, a; \boldsymbol{w})$$

DQNs: Experience Replay

- To help remove correlations, store dataset $\mathcal{D}$ from prior experience

s_1, a_1, r_1, s_2
s_2, a_2, r_2, s_3
s_3, a_3, r_3, s_4
...
s_t, a_t, r_t, s_{t+1}

$\longrightarrow$ s, a, r, s'

- To perform experience replay, repeat the following:
  - $(s, a, r, s') \sim \mathcal{D}$: sample an experience tuple from the dataset
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$$\Delta \boldsymbol{w} = \alpha(r + \gamma \max_{a'} \hat{Q}(s', a'; \boldsymbol{w}) - \hat{Q}(s, a; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s, a; \boldsymbol{w})$$

- **Can treat the target as a scalar, but the weights will get updated on the next round, changing the target value**

DQNs: Fixed Q-Targets

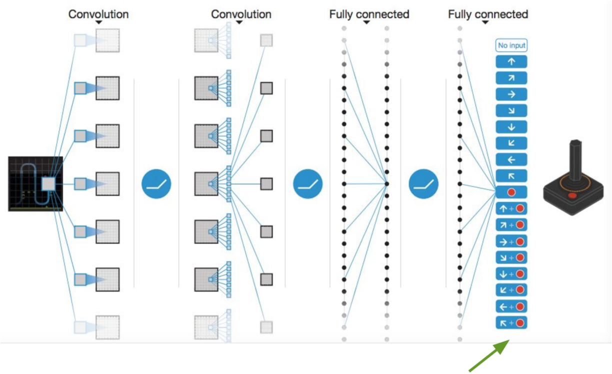
- To help improve stability, fix the **target weights** used in the target calculation for multiple updates
- Use a different set of weights to compute target than is being updated
- Let parameters $\boldsymbol{w}^-$ be the set of weights used in the target, and $\boldsymbol{w}$ be the weights that are being updated
- Slight change to computation of target value:
  - $(s, a, r, s') \sim \mathcal{D}$: sample an experience tuple from the dataset
  - Compute the target value for the sampled s: $r + \gamma \max_{a'} \hat{Q}(s', a'; \boldsymbol{w}^-)$
  - Use stochastic gradient descent to update the network weights

$$\Delta \boldsymbol{w} = \alpha(r + \gamma \max_{a'} \hat{Q}(s', a'; \boldsymbol{w}^-) - \hat{Q}(s, a; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s, a; \boldsymbol{w})$$

DQNs Summary

- DQN uses experience replay and fixed Q-targets
- Store transition $(s_t, a_t, r_{t+1}, s_{t+1})$ in replay memory $\mathcal{D}$
- Sample random mini-batch of transitions (s, a, r, s') from $\mathcal{D}$
- Compute Q-learning targets w.r.t. old, fixed parameters $\boldsymbol{w}^{-}$
- Optimizes MSE between Q-network and Q-learning targets
- Uses stochastic gradient descent

DQN



1 network, outputs Q value for each action

Figure: Human-level control through deep reinforcement learning, Mnih et al, 2015

Demo

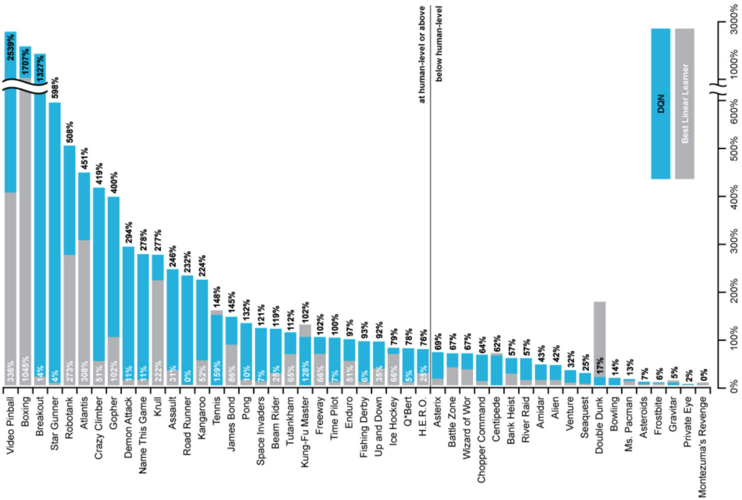


Figure: Human-level control through deep reinforcement learning, Mnih et al, 2015

Which Aspects of DQN were Important for Success?

Game	Linear	Deep Network	DQN w/ fixed Q	DQN w/ replay	DQN w/replay and fixed Q
Breakout	3	3	10	241	317
Enduro	62	29	141	831	1006
River Raid	2345	1453	2868	4102	7447
Seaquest	656	275	1003	823	2894
Space Invaders	301	302	373	826	1089

- Replay is **hugely** important
- Why? Beyond helping with correlation between samples, what does replaying do?

Deep RL

- Success in Atari has led to huge excitement in using deep neural networks to do value function approximation in RL
- Some immediate improvements (many others!)
  - **Double DQN** (Deep Reinforcement Learning with Double Q-Learning, Van Hasselt et al, AAAI 2016)
  - Prioritized Replay (Prioritized Experience Replay, Schaul et al, ICLR 2016)
  - Dueling DQN (best paper ICML 2016) (Dueling Network Architectures for Deep Reinforcement Learning, Wang et al, ICML 2016)

Double DQN

- Recall maximization bias challenge
  - Max of the estimated state-action values can be a biased estimate of the max
- Double Q-learning

Recall: Double Q-Learning

Initialize $Q_1(s,a)$ and $Q_2(s,a)$,$\forall s \in S, a \in A$ $t = 0$, initial state $s_t = s_0$

loop

  Select a_t using ϵ-greedy $\pi(s) = \arg\max_a Q_1(s_t, a) + Q_2(s_t, a)$

  Observe (r_t, s_{t+1})

  if (with 0.5 probability True) **then**

$$Q_1(s_t, a_t) \leftarrow Q_1(s_t, a_t) + \alpha(r_t + Q_1(s_{t+1}, \arg\max_{a'} Q_2(s_{t+1}, a')) - Q_1(s_t, a_t))$$

  else

$$Q_2(s_t, a_t) \leftarrow Q_2(s_t, a_t) + \alpha(r_t + Q_2(s_{t+1}, \arg\max_{a'} Q_1(s_{t+1}, a')) - Q_2(s_t, a_t))$$

  end if

  $t = t + 1$

end loop

Double DQN

- Extend this idea to DQN
- Current Q-network $\boldsymbol{w}$ is used to select actions
- Older Q-network $\boldsymbol{w}^-$ is used to evaluate actions

$$\Delta \boldsymbol{w} = \alpha(r + \gamma \overbrace{\hat{Q}(\underbrace{\arg\max_{a'} \hat{Q}(s', a'; \boldsymbol{w})}_{\text{Action selection: } \boldsymbol{w}}; \boldsymbol{w}^-)}^{\text{Action evaluation: } \boldsymbol{w}^-} - \hat{Q}(s, a; \boldsymbol{w}))$$

Double DQN

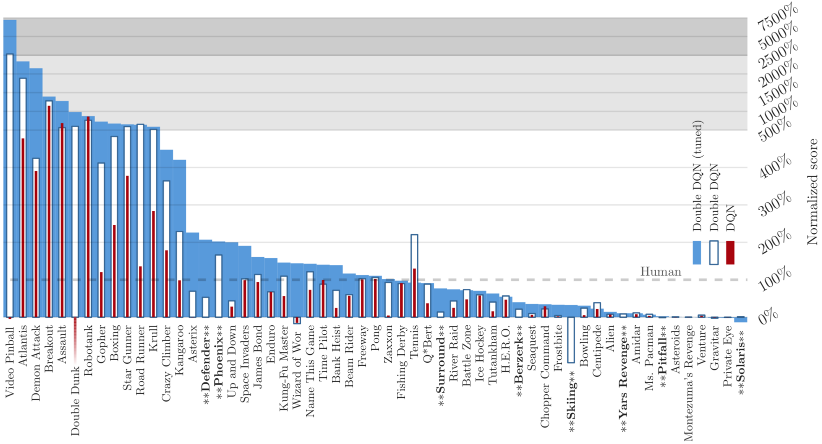


Figure: van Hasselt, Guez, Silver, 2015

Deep RL

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Refresher: Mars Rover Model-Free Policy Evaluation

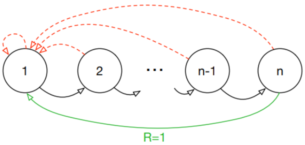
s_1	s_2	s_3	s_4	s_5	s_6	s_7
$R(s_1) = +1$ Okay Field Site	$R(s_2) = 0$	$R(s_3) = 0$	$R(s_4) = 0$	$R(s_5) = 0$	$R(s_6) = 0$	$R(s_7) = +10$ Fantastic Field Site

- Mars rover: R = [1 0 0 0 0 0 +10] for any action
- $\pi(s) = a_1\ \forall s$, $\gamma = 1$. any action from s_1 and s_7 terminates episode
- Trajectory = (s_3, a_1, 0, s_2, a_1, 0, s_2, a_1, 0, s_1, a_1, 1, terminal)
- First visit MC estimate of V of each state? [1 1 1 0 0 0 0]
- Every visit MC estimate of V of s_2? 1
- TD estimate of all states (init at 0) with $\alpha = 1$ is [1 0 0 0 0 0 0]
- Now get to chose 2 "replay" backups to do. Which should we pick to get best estimate?

Impact of Replay?

- In tabular TD-learning, **order** of replaying updates could help speed learning
- Repeating some updates seem to better propagate info than others
- Systematic ways to prioritize updates?

Potential Impact of Ordering Episodic Replay Updates



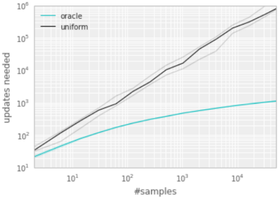


Figure: Schaul, Quan, Antonoglou, Silver ICLR 2016

- Schaul, Quan, Antonoglou, Silver ICLR 2016
- Oracle: picks (s, a, r, s') tuple to replay that will minimize global loss
- Exponential improvement in convergence
  - Number of updates needed to converge
- Oracle is not a practical method but illustrates impact of ordering

Prioritized Experience Replay

- Let i be the index of the i-the tuple of experience (s_i, a_i, r_i, s_{i+1})
- Sample tuples for update using priority function
- Priority of a tuple i is proportional to DQN error

$$p_i = \left| r + \gamma \max_{a'} Q(s_{i+1}, a'; \boldsymbol{w}^-) - Q(s_i, a_i; \boldsymbol{w}) \right|$$

- Update p_i every update
- p_i for new tuples is set to 0
- One method[1]: proportional (stochastic prioritization)

$$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$$

[1] See paper for details and an alternative

Check Your Understanding

- Let i be the index of the i-the tuple of experience (s_i, a_i, r_i, s_{i+1})
- Sample tuples for update using priority function
- Priority of a tuple i is proportional to DQN error

$$p_i = \left| r + \gamma \max_{a'} Q(s_{i+1}, a'; \mathbf{w}^-) - Q(s_i, a_i; \mathbf{w}) \right|$$

- Update p_i every update
- p_i for new tuples is set to 0
- One method[1]: proportional (stochastic prioritization)

$$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$$

- $\alpha = 0$ yields what rule for selecting among existing tuples?

[1] See paper for details and an alternative

Performance of Prioritized Replay vs Double DQN

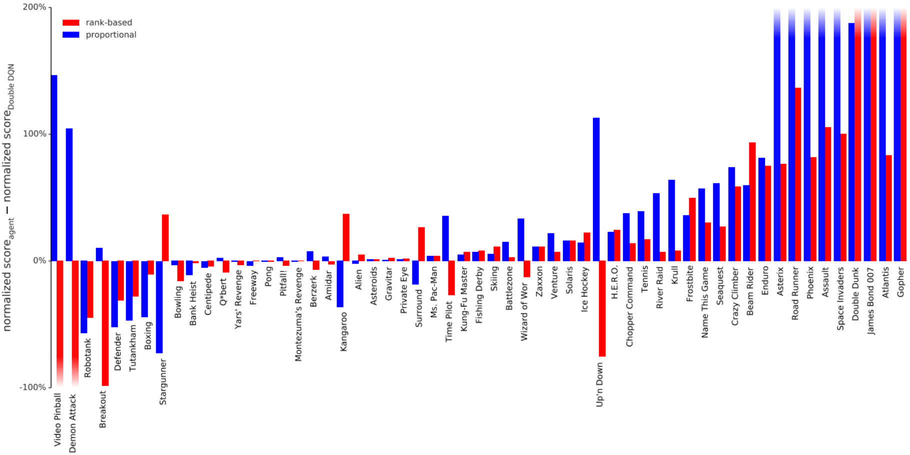


Figure: Schaul, Quan, Antonoglou, Silver ICLR 2016

Deep RL

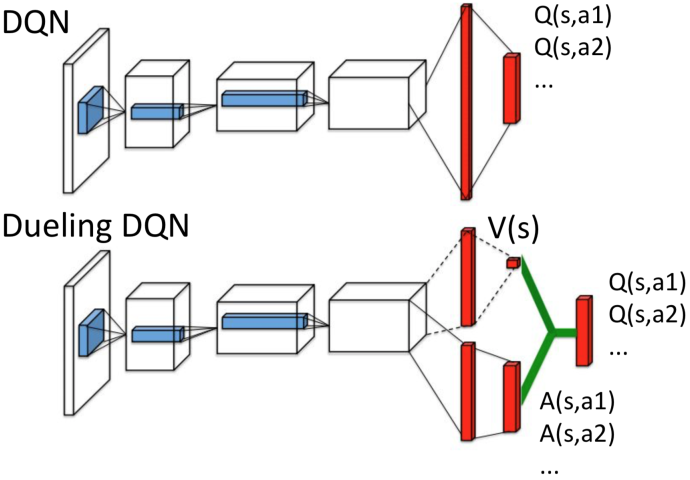
- Success in Atari has led to huge excitement in using deep neural networks to do value function approximation in RL
- Some immediate improvements (many others!)
  - DQN (Deep Reinforcement Learning with Double Q-Learning, Van Hasselt et al, AAAI 2016)
  - Prioritized Replay (Prioritized Experience Replay, Schaul et al, ICLR 2016)
  - **Dueling DQN** (best paper ICML 2016) (Dueling Network Architectures for Deep Reinforcement Learning, Wang et al, ICML 2016)

Value & Advantage Function

- Intuition: Features need to pay attention to determine value may be different than those need to determine action benefit
- E.g.
  - Game score may be relevant to predicting $V(s)$
  - But not necessarily in indicating relative action values
- Advantage function (Baird 1993)

$$A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$$

Dueling DQN



Wang et.al., ICML, 2016

Identifiability

- Advantage function

$$A^\pi(s,a) = Q^\pi(s,a) - V^\pi(s)$$

- Identifiable?

Identifiability

- Advantage function

$$A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$$

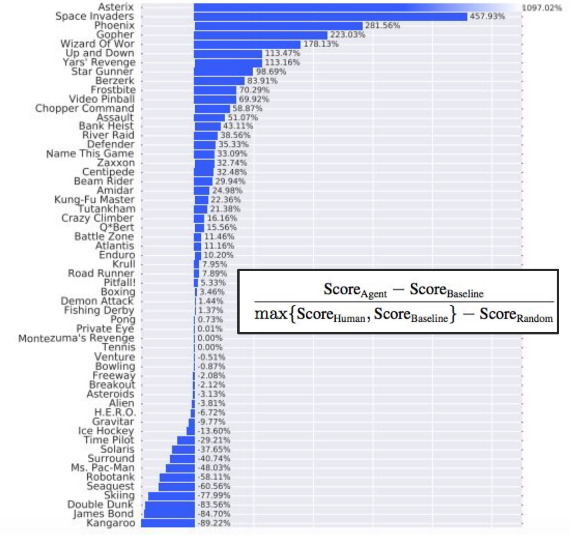
- Unidentifiable
- Option 1: Force $A(s,a) = 0$ if a is action taken

$$\hat{Q}(s,a;\boldsymbol{w}) = \hat{V}(s;\boldsymbol{w}) + \left(\hat{A}(s,a;\boldsymbol{w}) - \max_{a' \in \mathcal{A}} \hat{A}(s,a';\boldsymbol{w})\right)$$

- Option 2: Use mean as baseline (more stable)

$$\hat{Q}(s,a;\boldsymbol{w}) = \hat{V}(s;\boldsymbol{w}) + \left(\hat{A}(s,a;\boldsymbol{w}) - \frac{1}{|\mathcal{A}|}\sum_{a'} \hat{A}(s,a';\boldsymbol{w})\right)$$

Dueling DQN V.S. Double DQN with Prioritized Replay



$$\frac{\text{Score}_{\text{Agent}} - \text{Score}_{\text{Baseline}}}{\max\{\text{Score}_{\text{Human}}, \text{Score}_{\text{Baseline}}\} - \text{Score}_{\text{Random}}}$$

Figure: Wang et al, ICML 2016

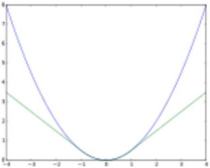
Practical Tips for DQN on Atari (from J. Schulman)

- DQN is more reliable on some Atari tasks than others. Pong is a reliable task: if it doesn't achieve good scores, something is wrong
- Large replay buffers improve robustness of DQN, and memory efficiency is key
  - Use uint8 images, don't duplicate data
- Be patient. DQN converges slowly—for ATARI it's often necessary to wait for 10-40M frames (couple of hours to a day of training on GPU) to see results significantly better than random policy
- In our Stanford class: Debug implementation on small test environment

Practical Tips for DQN on Atari (from J. Schulman) cont.

- Try Huber loss on Bellman error

$$L(x) = \begin{cases} \frac{x^2}{2} & \text{if } |x| \leq \delta \\ \delta|x| - \frac{\delta^2}{2} & \text{otherwise} \end{cases}$$



Practical Tips for DQN on Atari (from J. Schulman) cont.

- Try Huber loss on Bellman error

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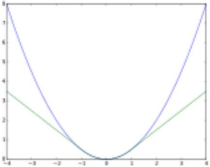

- Consider trying Double DQN—significant improvement from small code change in Tensorflow.
- To test out your data pre-processing, try your own skills at navigating the environment based on processed frames
- Always run at least two different seeds when experimenting
- Learning rate scheduling is beneficial. Try high learning rates in initial exploration period
- Try non-standard exploration schedules

Table of Contents

Class Structure

- Last time: Value function approximation
- This time: RL with function approximation, deep RL